
14 Human Brain–Computer Interface

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ABSTRACT

A brain–computer interface (BCI) transforms signals originating from the human brain into commands that can control devices or applications. In this way, a BCI provides a new nonmuscular communication channel, which can be used to assist patients who have highly compromised motor functions, as is the case with patients

suffering from neurological diseases such as amyotrophic lateral sclerosis (ALS) or brainstem stroke. The immediate goal of current research is to provide these users with an opportunity to communicate with their environment. Present-day BCI systems use different electrophysiological signals such as slow cortical potentials, evoked potentials, and oscillatory activity recorded from scalp or subdural electrodes, and cortical neuronal activity recorded from implanted electrodes. Due to advances in methods of signal processing, it is possible that specific features automatically extracted from the electroencephalogram (EEG) and electrocorticogram (ECoG) are used to operate computer-controlled devices. The interaction between the BCI system and the user, in terms of adaptation and learning, is a challenging aspect of any BCI development and application. This chapter outlines and explains current approaches and methods used in BCI research.

14.1 INTRODUCTION

A technical system that permits direct communication between brain and computer is known as a BCI.^{1,2} In this case, the normal communication channels, such as speech and movement, are not used, but instead the brain activity is directly recorded and transformed into a control signal. Therefore, a BCI provides a new communication channel that can be used to convey messages and commands directly from the brain to the external world. The use of a BCI depends on the interaction of two adaptive controllers, the user's brain and a computer, which has to produce an action that accomplishes the user's intention.

One general base for a BCI is that music or visual or motor imagery modifies neuronal activity and can result in measurable changes in firing patterns of cortical neurons and in the ongoing EEG and ECoG.^{3,4} Furthermore, focused or selective attention can enhance different brain signals or components of evoked potentials and in turn can be used in a BCI system.⁵ Beside electrical potentials, the blood oxygen level dependent (BOLD) response measured by real-time functional magnetic resonance imaging (fMRI) can be used as an input signal for a BCI.⁶

The current and most important applications of a BCI are the restoration of a communication channel for patients with a locked-in syndrome and the control of neuroprosthesis in patients with spinal cord injury. Aside from these, there are the important and established field of neurofeedback therapy and the upcoming field of multimedia and virtual reality applications. In this context, a BCI could be used for diverse tasks such as playing games or providing multidimensional feedback in virtual reality. Concerning the last point, BCI adds a new dimension in man-machine interaction and may be of great importance in multimedia applications.

A BCI system is, in general, composed of the following components: signal acquisition, preprocessing, feature extraction, classification (detection), and application interface (Figure 14.1). The signal acquisition component is responsible for recording the electrophysiological signals providing the input to the BCI. Depending on the type of analyzed brain signals and the processing mode, sensory stimulation may be necessary. The task of preprocessing is to enhance the signal-to-noise ratio.

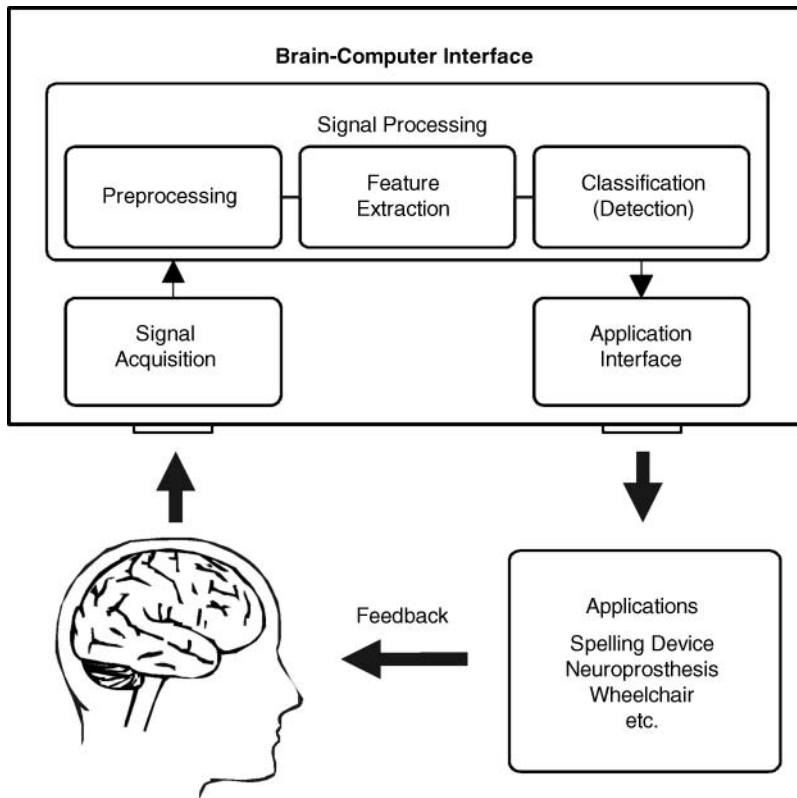


FIGURE 14.1 Components of a BCI system: signals from the user's brain are acquired and processed to extract specific features used for classification. The classifier output is transformed into a device command, which, at the same time, provides feedback to the user.

This can include artifact reduction methods and the application of advanced signal processing methods. After preprocessing, the signal is subjected to the feature extraction algorithm. The goal of this component is to find a suitable representation (signal features) of the electrophysiological data that simplifies the subsequent classification or detection of brain patterns. That is, the signal features should encode the commands sent by the user, but should not contain noise and other patterns that can impede the classification process. There are a variety of feature extraction methods used in current BCI systems. A list (not exhaustive) of these methods includes amplitude measures, band power, Hjorth parameters, autoregressive models, and wavelets.

The task of the classifier component is to use the signal features provided by the feature extractor to assign the recorded samples of the signal to a category of brain patterns. In the simplest form, detection of a single brain pattern is sufficient,

for instance, by means of a threshold method.^{7,8} More sophisticated classifications of different patterns depend on linear or nonlinear classifiers.⁹

The classifier output, which can be a simple on–off signal or a signal that encodes a number of different classes, is transformed into an appropriate signal that can then be used to control a variety of devices. For most current BCI systems, the output device is a computer screen and the output is the selection of certain targets. Advanced applications include the controlling of spelling systems or other external apparatuses such as prosthetic devices and multimedia applications.

Many BCI systems, including animal applications,¹⁰ use immediate feedback of performance. In human applications feedback of performance is usually given by visualization of the brain signal on a computer screen or the presentation of an auditory or tactile analogue of the actual brain response (mu rhythm, slow cortical potential, or other EEG activity).

The mode of operation determines when the user performs a mental task and intends therewith to transmit a message. In principle, this step can be divided into two distinct modes of operation, the first being externally paced (cue-based, computer-driven, synchronous BCI) and the second being internally paced (noncue-based, user-driven, asynchronous BCI). In the case of a synchronous BCI, a fixed, predefined time window is used. After a visual or an auditory cue stimulus, the subject has to act and produce a specific mental state. Nearly all known BCI systems work in such a cue-based mode.^{9,11,12} An asynchronous protocol requires a continuous analysis and feature extraction of the recorded brain signal. Thus, such BCIs are, in general, even more demanding and more complex than BCIs operating with a fixed timing scheme. In a synchronous BCI, for example, only two mental tasks or two brain states have to be differentiated, whereas in an asynchronous BCI, a third brain state has to be identified, which is the resting or idling state, also referred to as zero class. To date, only a few BCI research groups are working on an asynchronous BCI.^{8,13–18}

14.2 BRAIN SIGNALS

In principle, there are invasive and noninvasive methods used to record brain signals. The EEG, a noninvasive method, records electrical potential changes and reflects the common activity of several millions of neurons extending over some square centimeters of the cortical tissue. Invasive methods are exemplified by the ECoG as well as by intracortical recordings. In contrast to the EEG, the ECoG represents integrated bioelectrical activity over a much smaller cortical area, but still constitutes the common activity of many thousands of neurons. The multichannel intracortical recordings reflect extracellular activity generated by small neuronal populations in the order of about 100 cells or fewer.^{19,20}

In the EEG, as well as in the ECoG, two types of phenomena need to be differentiated:

1. Event-related potentials (ERPs), including evoked potentials and slow cortical potential (SCP) shifts
2. Event-related changes in ongoing EEG/ECOG activity in specific frequency bands

Event-related desynchronization (ERD) defines an amplitude (power) decrease of a rhythmic component, whereas event-related synchronization (ERS) characterizes an amplitude (power) increase.²¹

In a simplified form it may be assumed that ERPs represent the summative responses of cortical neurons due to changes of the afferent activity, while ERD and ERS reflect changes in the activity of local interactions between main neurons and interneurons that control the frequency components of ongoing EEG/ECOG components.

Slow cortical potentials are slow shifts of the EEG with a duration from 300 msec to several seconds. The amplitude on the scalp may vary between 1 and 100 μ V in the case of pre-epileptic or epileptic activity. The family of SCPs includes the so-called contingent negative variation (CNV), premovement potentials, the Bereitschaftspotential,²² and expectancy waves.²³

The family of SCPs originates in the upper layers (layers I and II) of the cortex. However, slow potential changes, probably of the same origin, can be found in all parts of the nervous system. Whether the mechanisms of physiological generation are the same is still a matter of debate. The apical dendrites receive most of their input from intracortical fibers, callosal input from the other hemisphere, and input from the medial and reticular thalamus, the so-called nonspecific ascending activation system. Cholinergic inflow to the apical dendrites arrives primarily from structures in the basal forebrain and the basal ganglia.²⁴ The amplitudes of slow cortical potentials are highly sensitive to the manipulation of cholinergic, monoaminergic, and glutamatergic transmission. SCPs tending toward the negative reflect slow EPSP and glial potentials and, therefore, indicate longer-lasting depolarization of the dendritic network. SCPs tending toward the positive are more difficult to analyze because they may result from a reduction of inflow to the apical dendrites, or, probably in rare occasions, from direct inhibitory activity at the level of layer I or II. Finally, SCPs tending toward the positive may indicate the inversion of the cortical dipole between the upper input layers and the lower output layers of the cortex.²⁵ Therefore, the interpretation of slow potentials tending toward the positive requires a description of the experimental and physiological context of recording. Note also that in areas where the convexity of the cortex results in an inversion of the usual cortical dipole directions, such as in the orbitofrontal cortex, the inferior temporal cortex, part of area 17 of the occipital cortex, and the interhemispheric sulcus, inversion of the polarity of slow cortical potentials may be found. Therefore, polarity changes recorded at electrodes from the scalp alone can only be interpreted with great caution. Birbaumer et al.²⁴ have described a frontal corticothalamic and basal ganglia network responsible for the attentional regulation of all types of preparatory SCPs. They have shown that slow cortical potentials are part of an excitatory and

inhibitory threshold regulation mechanism involving an extended frontothalamo basal ganglia cortex loop, whose anatomy was described by Braitenberg and Schüz.²⁶ In sum, negative SCPs indicate a preparatory state of the underlying cortical network, but they reflect not only motor preparation but also preparation for cognitive and emotional activity.

Changes of the oscillatory brain activity, referred to as ERD/ERS, may reflect the general characteristic of cortical populations of neurons either to work in synchrony or not. Coherent or synchronous activity results in large potential amplitudes in EEG, whereas incoherent behavior leads to desynchronized patterns. One important prerequisite for the occurrence of oscillations in the EEG might be the interconnectivity between networks and the formation of feedback loops. In general, it can be stated that small synchronized populations of neurons with short feedback loops (e.g., intracortical) may be responsible for low-amplitude and high-frequency oscillations in the EEG (e.g., gamma activity), whereas large synchronized populations with relatively long feedback loops (e.g., thalamocortical) lead to high-amplitude oscillations (e.g., alpha rhythm). Therefore, various components in the EEG (alpha, beta, and gamma) show different reactivity patterns. For example, in contrast to the mu desynchronization (mu ERD), which lasts some seconds, the induced gamma oscillations (gamma ERS) are short lasting and clearly embedded in the mu ERD (see Color Figure 14.2*). It seems that the desynchronization of large population of neurons in widespread networks (alpha or mu ERD) might be the prerequisite for a synchronization of small populations in localized networks.

The gamma ERS occurring during movement execution in the EEG is small-banded and composed of frequency components around 40 Hz (Color Figure 14.2A; see also Pfurtscheller and Neuper²⁷), whereas the gamma ERS in the ECoG is more broad-banded, including frequency components from 60–90 Hz (Color Figure 14.2C; see also Crone et al.²⁸ and Pfurtscheller et al.²⁹). Short-lasting bursts of beta oscillations in the range of approximately 14–30 Hz (beta ERS) can be found as a rebound phenomenon after active movement and somatosensory stimulation,³⁰ but also after motor imagery.³¹ An example for such a beta ERS is displayed in Color Figure 14.2B.

It is important to notice that the detection of an amplitude decrease within a single EEG (ECoG) trial is not always a simple task. In contrary, the detection of an amplitude increase in the form of bursts or induced oscillations (ERS pattern) within predefined frequency bands can be performed much more easily. This speaks strongly in favor of focusing a BCI on the detection of ERS patterns and ERPs. Successful detection of mentally induced beta oscillations has been already reported in BCI research. A tetraplegic patient, exemplarily, was able to induce 17-Hz oscillations by foot motor imagery, after some months of training. Consequently, he was able to control the opening and closing of a hand orthosis³² and to perform grasping functions by means of functional electrical stimulation³³ (for details, see Section 14.9). Another example of a high-classification accuracy obtained in a specific BCI system is the induction of 10-Hz oscillations over the hand representation area during imagination of foot movements.³⁴ In this case a weak ERD over the foot representation area is accompanied by a phenomenon resembling a “lateral inhibition”

* See color insert following page 170.

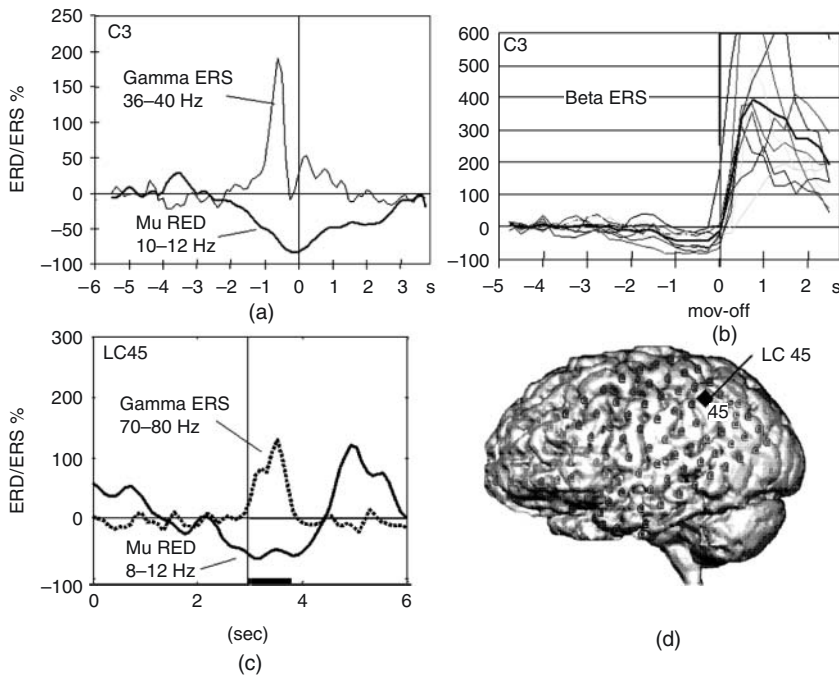


FIGURE 14.2 (see color figure) (a) Simultaneous ERD/ERS in the mu (10–12 Hz) and gamma bands (36–40 Hz) recorded from the left sensorimotor area and processed synchronous to the offset of voluntary right finger movements. (b) Superimposed ERD/ERS time courses from individual subjects (thin lines) and grand average curve (thick line) calculated for subject-specific beta frequency bands. Data were recorded on electrode C3 and processed synchronous to the offset of wrist movements. (c) Simultaneous ERD/ERS in the mu (8–12 Hz) and gamma (70–80 Hz) band in ECoG recordings during voluntary finger movement. (d) ECoG electrode locations.

mechanism in the form of laterally induced 10-Hz oscillations. This phenomenon has been referred to as “focal ERD/surround ERS” by Lopes da Silva and linked to a thalamic gating mechanism.³⁵

14.3 MOTOR IMAGERY AS MENTAL STRATEGY FOR A BCI

Research work in recent years has shown that imagination of movement activates similar cortical areas and shares similar temporal characteristics as the execution of the same movement.³⁶ A number of fMRI studies reported similarities between the preparation of self-paced movement and motor imagery.^{37–39} However, distinct processes may be involved: besides the activation of various motor areas during the imagination of movement, the importance of a perceptual or visuo-spatial component should be stressed, since motor imagery probably involves visual and kinesthetic internal representations.⁴⁰ In this respect it is of interest that even observation of a movement can activate premotor areas.^{41,42} The latter finding underlines the importance of a visuospatial component in motor cortex function and provides evidence

for the existence of an action observation/execution matching system. This point is of particular importance when considering the effects of visual feedback during the operation of a BCI, and will be discussed in more detail below (Section 14.6).

Several EEG studies indicate that primary sensorimotor areas are activated when subjects imagine the execution of a hand movement. Klass and Bickford⁴³ and Chatrian et al.⁴⁴ have already observed a blocking or desynchronization of the central mu rhythm with motor imagery. Quantification of the temporal–spatial pattern of ERD clearly showed that one-sided hand motor imagery can result in a lateralized activation of sensorimotor areas, as found in the planning and preparatory phases of a self-paced hand or finger movement.³¹ Furthermore, measurements of slow cortical potential shifts⁴⁵ have shown that similar changes over the contralateral hand area can be observed during execution and imagination of movement. The evaluation of movement-related potentials in Parkinson’s disease revealed similar potentials during motor imagery and during preparation of a real movement.⁴⁶ Also, multi-channel neuromagnetic measurements demonstrated the effect of motor imagery on brain oscillations generated in primary motor areas.⁴⁷

The grand average ERD/ERS curves in Figure 14.3 show different reactivity patterns from able-bodied subjects during right and left hand movement imagery. The alpha ERD is long-lasting and recovers slowly to the baseline; the beta ERD is of shorter duration and is followed by a beta ERS over the contralateral side. The fact that the imagination of a movement can result in a beta ERS is of interest for the general interpretation of this phenomenon, because of the lack of afferent input during motor imagery. The processing of somatosensory afferent input, though, has been assumed to play an important role for the beta ERS.⁴⁸

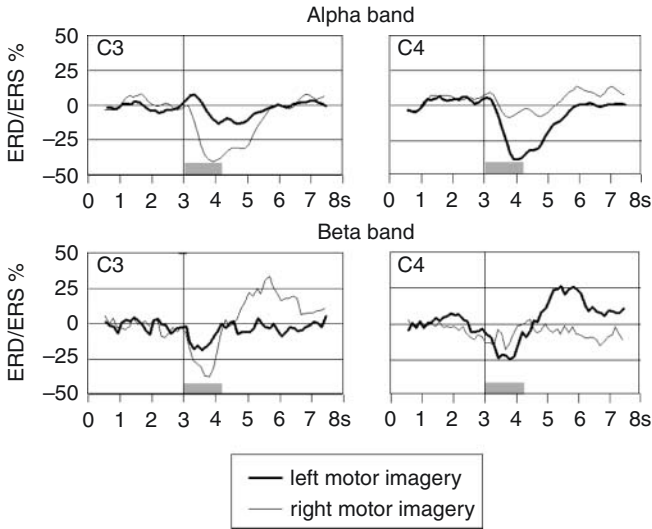


FIGURE 14.3 Grand average ERD/ERS curves recorded from the left (C3) and right sensorimotor cortex (C4) and calculated in the alpha/mu (upper panels, $n = 16$) and beta range (lower panel, $n = 9$). A gray bar indicates the time period of cue presentation. (From Reference 31, with permission.)

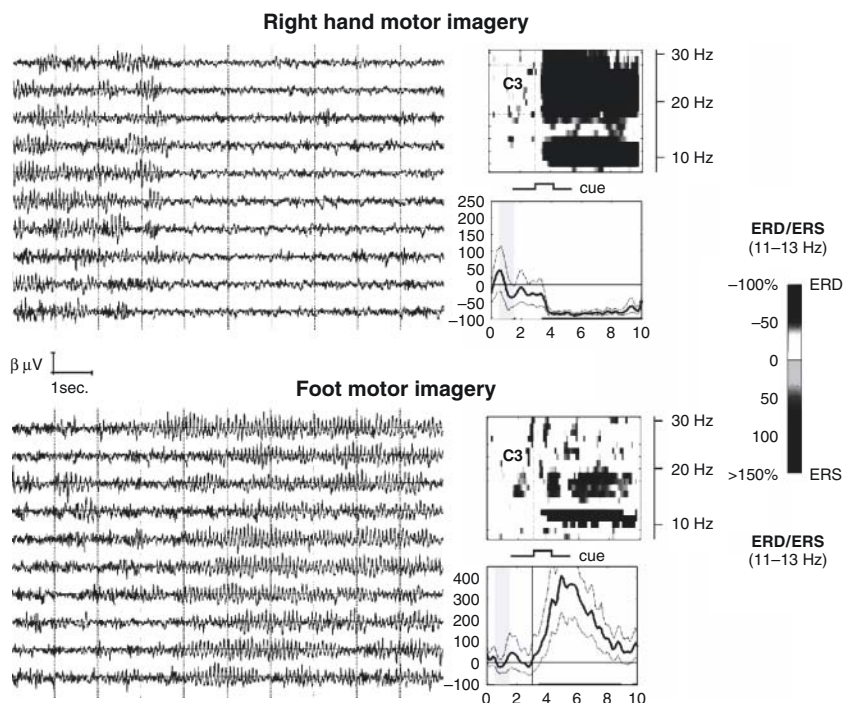


FIGURE 14.4 (see color figure) Left side: Examples of single EEG trials recorded from electrode position C3 during right hand (upper panel) and foot (lower panel) motor imagery. Right side: ERD/ERS time frequency maps and time curves of the frequency band 11–13 Hz recorded from electrode position C3 during right hand (upper panels) versus foot (lower panels) motor imagery. Onset of cue presentation at second 3.

Color [Figure 14.4](#) illustrates how various types of motor imagery can result in different reactivity patterns on one electrode location over the sensorimotor area. Whereas, for instance, right hand motor imagery can block mu and beta rhythms over the left sensorimotor cortex (Color [Figure 14.4](#), upper panel), foot motor imagery can have an opposite effect — namely, it can induce mu oscillations (Color [Figure 14.4](#), lower panel). Parallel to the mu ERS, the beta activity is, in this case, moderately desynchronized. This example demonstrates that frequency-specific reactivity patterns in the ongoing EEG make it possible to distinguish between different types of motor imagery.

In summary, it can be stated that motor imagery can modify sensorimotor rhythms in a manner similar to that observed in the preparatory phase of a movement that is actually executed. Since motor imagery results in somatotopically organized activation patterns, mental imaginations of different movements (e.g., left versus right hand, hand versus foot) can be an efficient strategy for operating a BCI based on oscillatory EEG activity. The challenge is to detect the imagery-related changes in ongoing, not-averaged EEG recordings.

14.4 SELF-REGULATION OF SLOW CORTICAL POTENTIALS AS A CONTROL STRATEGY FOR SPELLING DEVICES AND NEUROPROSTHESES

The mechanisms underlying the self-regulation of SCPs used for BCI systems has been intensively studied over the past 25 years.^{24,49} The self-regulation of SCPs was originally derived from animal experiments, where monkeys were positively reinforced for producing increases or decreases of slow preparatory potentials.^{50,51} Earlier, Fetz⁵² had already shown that monkeys can learn to regulate neuronal firing rates. As in animals, self-regulation of slow cortical potentials does not require continuous feedback of the neurophysiological response, but the reward of required amplitude changes in positive or negative polarity is a necessary ingredient of the learning process. Therefore, self-regulation of SCPs can be conceptualized as an implicit learning mechanism involving elements of classical and operant conditioning. It is not surprising that cognitive factors such as intelligence, motor imagery ability, age, personality characteristics, or particular imagery strategies are not critical for the performance in the slow potential self-regulation task and in the thought translation device (see [Section 14.5.3](#)). What has been shown to be a critical ingredient is the functional intactness of an extended frontocortical, basal ganglia attention regulation system and motivational factors such as reward value and schedules of reinforcement. Patients with a lesioned prefrontal lobe or with frontal lobe dysfunctions, such as schizophrenics and children with attention deficit disorder or other frontoregulatory deficits, show substantial delay or inability to regulate SCPs.

Color [Figure 14.5](#) shows fMRI of ten highly successful subjects during the regulation of positive- and negative-tending SCPs (unpublished results; see also Hinterberger et al.⁵³). As can be seen and as predicted from threshold regulation theory,²⁴ negative SCPs correlate with an increase of the BOLD response in several cortical areas of the frontal motor and nonmotor areas, while positive potentials covary with a decrease of the BOLD response in most cortical areas. Successful self-regulation of SCPs at the cortex can be predicted with high accuracy ($r > 0.9$) from the activation of the most likely inhibitory structures in the basal ganglia (putamen/pallidum) and deactivation of premotor areas. Subjects and patients therefore use an attentional threshold regulation mechanism to manipulate the excitation threshold of the cortex, as reflected in negative- and positive-tending SCPs.

In a study of motor imagery with healthy subjects⁵⁴ it was shown that subjects explicitly instructed to use activating motor imagery for negative SCPs and passive motor imagery for positive SCPs did not profit in the speed of acquisition of the learned cortical response. The groups with or without imagery achieved the same level of performance. However, in intractable epilepsy it was shown that patients with extremely high levels of negative polarized SCPs do not profit from self-regulation training.⁵⁵ In addition, operant learning of SCP control was shown to be a prerequisite for correct psychophysical scaling of the subjects' own cortical potentials.⁵⁵ Only subjects with a high level of performance were able to estimate their own cortical polarization subsequent to achieving high performance. Correct self-estimation and scaling of the ongoing brain state and verbal descriptions of imagery

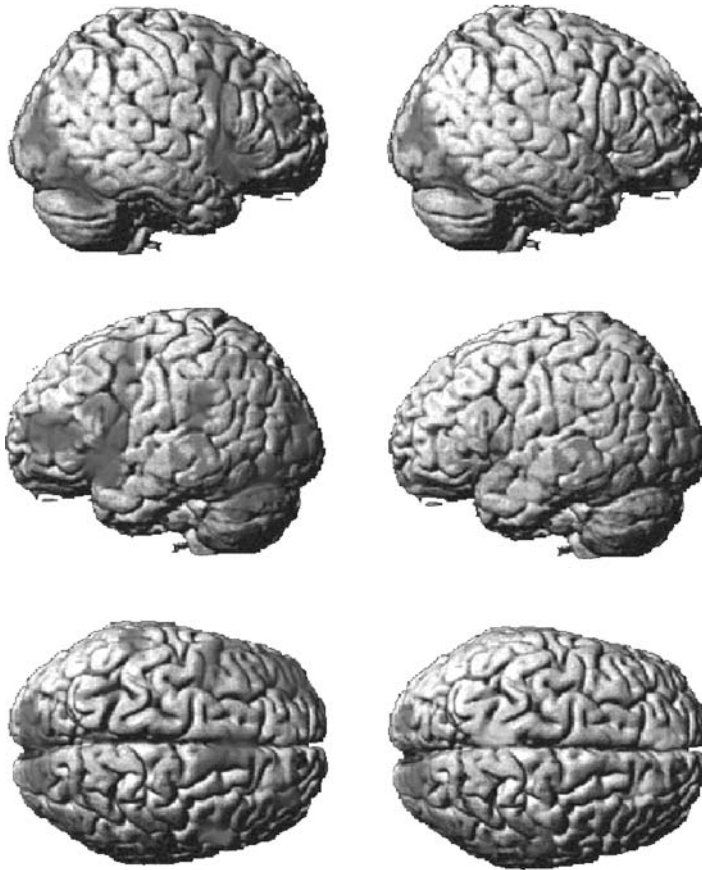


FIGURE 14.5 (see color figure) Averaged functional magnetic resonance images (fMRI) of ten subjects during self-regulation of cortical negativity (left) and positivity (right). Red symbolizes increase and green symbolizes decrease of BOLD response.

used for self-regulation of SCPs are thus a consequence and not a cause of successful learning.

14.5 A SHORT OVERVIEW OF EEG-BASED BCI SYSTEMS

EEG-based BCIs can be realized in an externally paced or an internally paced mode. On the one hand, changes of oscillatory EEG activity as ERD and ERS^{9,56} are analyzed and classified; on the other, various types of ERPs are detected by BCI systems. To the latter belong the SCP,⁷ the visual evoked potential,⁵⁷ the P300 component,⁵⁸ and the steady-state visual evoked potential.⁵⁹

14.5.1 THE WADSWORTH BCI

With the BCI system of Wolpaw, McFarland, and their colleagues,^{56,60,61} people with or without motor disabilities learn to control mu or beta rhythm amplitude and use

that control to move a cursor in one or two dimensions to targets on a computer screen. For each dimension of cursor movement, a linear equation translates mu or beta rhythm amplitude at one or several scalp locations into cursor movement ten times per second. Users learn in a series of 40-minute sessions to control the cursor. They complete 2 to 3 sessions per week. Most (about 80%) gain significant control in two to three weeks. In their first sessions, most use some kind of motor imagery (such as imagination of hand movements, whole body activities, or relaxation) to control cursor movement. As their training progresses, imagery typically becomes less important, and users move the cursor like they perform conventional motor acts, i.e., without thinking about the details of the performance.

Although EEG from only 1 or 2 scalp locations determines cursor movement online, data from 64 locations over the entire scalp are stored for later offline analysis that defines the complete topography of EEG changes associated with target position and helps to design improvements in online operation. This analysis relies mainly on r^2 , which is the proportion of the total variance in mu or beta rhythm amplitude that is accounted for by target position, and therefore indicates the user's level of EEG control. The r^2 topographical and spectral analyses demonstrate that control is sharply focused over sensorimotor cortex and in the mu or beta rhythm frequency bands. With this control, users can move the cursor to answer spoken "yes/no" questions with accuracies greater than 95%.^{62,63} In addition, they can also achieve independent control of two different mu or beta rhythm channels and use that control to move a cursor in two dimensions.¹² Recent work has focused on further improving one-dimensional control, and on applying it to selecting among up to eight different targets. Users have reached information transfer rates up to 20–25 bits per minute.⁶⁴

Research with the Wadsworth BCI has concentrated on defining the topographical, spectral, and temporal features of mu and beta rhythm control and on improving the mutually adaptive interactions between the user and the BCI system. The improvements include spatial filters that conform to the spatial frequencies of the user's mu or beta rhythms; autoregressive frequency analysis, which provides higher resolution for short time segments and therefore allows more rapid device control; and better selection of the constants in the equations that translate EEG control into cursor control.^{61,65,66} Current studies are also exploring incorporation of other EEG features into this BCI. For example, in trained users, errors in target selection are accompanied by a positive potential centered at the vertex.⁶⁷ This error potential might be useful for recognizing and canceling mistakes. While work up until now has used cursor movement as a prototype BCI application and has focused on improving it, effort is also being committed to specific applications such as verbal communication.^{62,63,68}

14.5.2 THE GRAZ BCI

The Graz BCI is an EEG-based system using motor imagery as the appropriate mental control strategy. Therefore, it uses electrode positions located over sensorimotor areas. Another characteristic feature of the Graz BCI is the usage of a classifier to discriminate between brain states associated with different types of motor imagery. Such a classifier has to be set up by a great number of examples of imagery-induced

EEG patterns obtained in sessions without feedback, following the timing of the cue-based standard paradigm (as shown in Figure 14.6). During the feedback sessions, the EEG is analyzed and classified in predefined time windows and the feedback is then given in real time. In the course of the training, the computer (classifier) is repeatedly adapted to the user's brain signals (Figure 14.7).

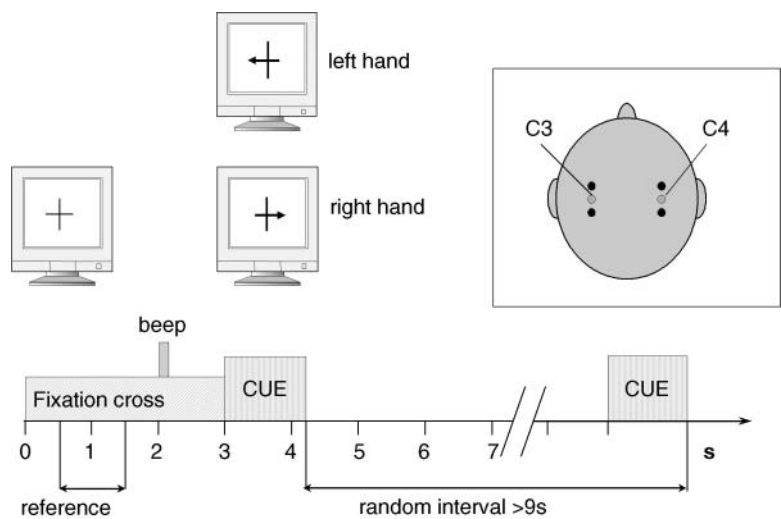


FIGURE 14.6 Imagination paradigm. The cue stimulus in the form of an arrow indicates the side of imagination. Insert: Bipolar channels close to electrode positions C3 and C4 as used in BCI experiments.

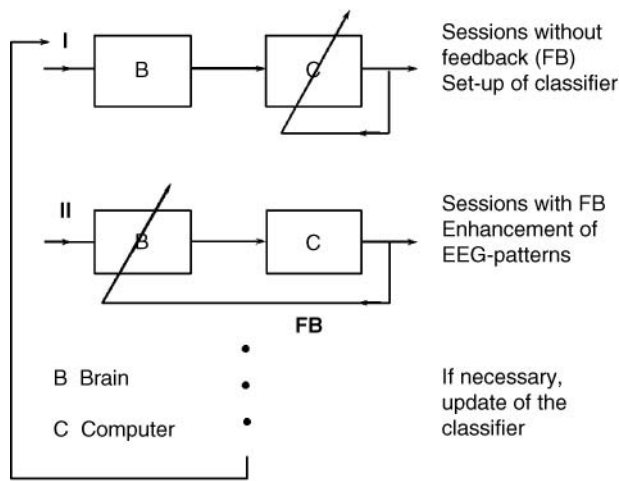


FIGURE 14.7 Types of brain–computer interactions. In a first stage (I), sessions without feedback are performed to collect data to set up a classifier. The computer learns to recognize different brain states. As soon as a classifier is available, feedback can be provided to the user (II), which modifies brain activity.

One of the first EEG-based BCI systems developed by Graz was able to discriminate between three brain states.⁶⁹ The subject was instructed to execute a specific movement (right hand, left hand, right foot) in the first three sessions and to imagine the same movement in the next two sessions. Band power (5–35 Hz) was estimated in intervals of 250 msec from three bipolar EEG channels. Four power estimates of each of the three channels were concatenated to form 12-dimensional vectors that were presented to a neural network-based classifier. The nonlinear classifier was trained with examples from the first sessions without feedback. The on-line results from the motor imagery sessions with feedback varied around 50% (the worst case of classification accuracy was 33.3%).

The next approach of the Graz BCI was to select the input features for each subject by using distinction-sensitive learning vector quantization (DSLQVQ).⁷⁰ This method is a valuable tool for the automatic selection of the most relevant frequency components and the most relevant electrode positions. Subject-specific frequency band selection raised the on-line classification accuracy by almost 10%.⁷¹ No frequency band selection is necessary when a parametric method is used for parameter estimation. Especially suitable for the modeling of the dynamics of brain signals is the adaptive autoregressive (AAR) parameter estimation using the Kalman algorithm.^{72–74} Time courses demonstrating the separability between two motor imagery tasks by adaptive autoregressive parameters and linear discriminant analysis (LDA) are displayed in [Figure 14.8](#).

Besides neural networks and linear classifiers, hidden Markov models (HMMs) are also suitable in BCI research.^{75,76} The HMM itself could be seen as a finite automata containing discrete steps and emitting a feature vector that depends on the current state of every time point, whereby each feature vector is modeled by Gaussian mixtures. The transition probabilities from one state to the other state are described using a transition matrix. A one-state HMM was used to implement an EEG-based spelling device, also called the “virtual keyboard.”⁷⁶ The feature vector was composed of logarithmic band power values estimated in two bipolar EEG channels, recorded over the sensorimotor area during two types of motor imagery. The subject’s task was to copy presented words (copy spelling) by selecting single letters out of a predefined alphabet. The structure of the virtual keyboard contains 5 decision levels for the selection of 32 letters and 2 further levels for confirmation and correction: in 5 successive steps the letter set was split into 2 equally sized subsets, until the subject selected a certain letter, and 2 further steps allowed the subject to confirm or correct this selection. In a first experiment, 3 able-bodied subjects achieved a spelling rate of 0.67 to 1.02 letters per minute.⁷⁶ Current studies focus on improving the spelling rate — for instance, by considering the probability of each letter and by shortening the trial length.

For the preprocessing of multichannel EEG recordings, the method of common spatial patterns (CSPs) was successfully used.⁷⁷ This is a supervised method and requires data sets divided into two groups from which each belongs to one of two brain states (i.e., motor imagery tasks).⁷⁸

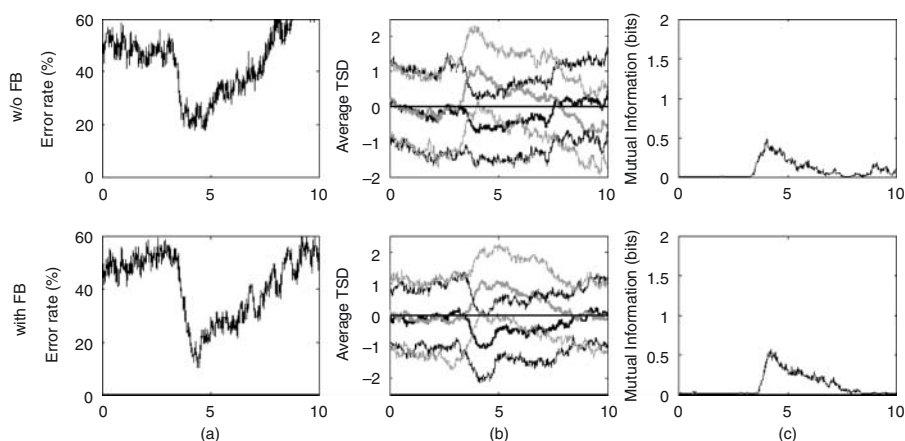


FIGURE 14.8 Time courses of one subject displaying the separability between two classes. Adaptive autoregressive (AAR) parameters (order $p = 6$) from bipolar channels close to C3 and C4, estimated with Kalman filtering, from the first session (without feedback; time interval 4.008–4.125 sec) were used to classify the EEG signals in the second session in order to provide online feedback. (a) Time courses of the error rate. $ERR(t)$ gives the classification error with LDA at time t , calculated with a jackknife method (leaving one trial out for testing). (b) Averaged time-varying signal distance (TSD), calculated as linear combination of AAR(6) parameters, for the left (dark) and right (light) trials. The average TSD curves (thick lines) clearly show a different behavior during imagined left and right hand movement. The thin lines represent the within-class standard deviation (SD) of the TSD and indicate the inter-trial variability of the EEG patterns. (c) Mutual information between the TSD and the class relationship. The entropy difference of the TSD with and without class information was calculated for every time step. This gives a time course of the mutual information in bits per trial.

14.5.3 THE THOUGHT TRANSLATION DEVICE

The thought translation device (TTD) is a brain–computer interface based on self-regulation of SCPs. The system was first described by Birbaumer et al.⁷⁹ and Elbert et al.⁸⁰ In the clinical context it was first applied in intractable and drug-resistant epilepsies^{23,81} and was later used as a communication device for completely paralyzed, locked-in patients.⁸² Other BCI systems using SCPs, primarily movement related potentials, are described by Müller et al.⁸³ These BCI systems do not include a training phase, but aim instead to classify the ongoing SCPs on-line with the use of motor imagery similar to the method employed by Pfurtscheller (Graz BCI; see [Section 14.5.2](#)) and Wolpaw (Wadsworth BCI; see [Section 14.5.1](#)). In the TTD, subjects receive visual, auditory, or tactile feedback from their SCPs on-line over a period from 1 to 10 sec, depending on the clinical or experimental purpose of the experiment.

[Figure 14.9](#) shows the basic principle in the case of visual feedback. The illumination of the upper goal on a screen indicates that a negative cortical potential should be produced and the illumination of the lower part of the screen signals that

a positive SCP needs to be obtained. The technical requirements for the TTD are DC amplifiers or EEG amplifiers with a long time constant (minimum 5 sec), simultaneous recording and correction of eye movements, and careful preparation of electrodes and electrode sites. The subjects or patients usually are trained over periods of several hours to months to achieve a high performance level of voluntary self-regulation of SCPs (in the case of communication devices for the paralyzed, a minimum performance level of 75% correct trials is necessary). After having achieved the necessary performance level, subjects are confronted with the so-called language support program (LSP), consisting of a sophisticated hierarchical spelling system that allows the patient to select letters, words, or entire sentences.⁸⁴ Most paralyzed patients use positive SCPs originating from premotor and motor areas of the brain. The electrode location is usually at Cz or between Fz and Cz. Electrode location may vary according to patient requirements and clinical characteristics. Since completely locked-in patients often can no longer follow visual signals, the TTD is equipped with an auditory and tactile feedback system which enables the patient to listen to his or her own brain activity, transformed into high- or low-pitched tones and harmonic tone sequences that function as reward.

Thought Translation Device (TTD)

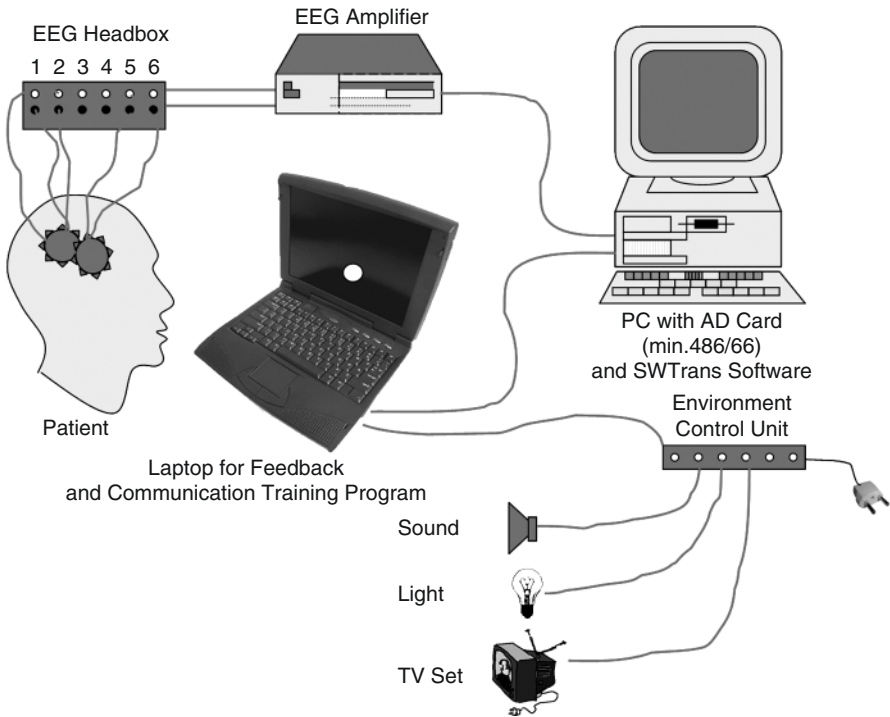


FIGURE 14.9 The thought translation device (TTD).

14.5.4 OTHER BCI SYSTEMS

An interesting approach to a communication system was introduced by Farwell and his colleagues.⁵ It is based on the fact that infrequent or particularly significant auditory, visual, or somatosensory stimuli, when interspersed with frequent standard stimuli, typically evoke in the EEG over the parietal cortex a positive peak at about 300 msec termed the P300 component or “oddball” response.⁵ The user is confronted with a 6×6 letter matrix. In short intervals one of the rows or one of the columns of the matrix is flashed. The user makes a selection by focusing the desired letter and counting how many times the respective row or column flashes. Only in the responses elicited by the desired choice a prominent P300 is visible, and the BCI uses this effect to determine the user’s selection. With this system a communication rate of about seven items per minute can be obtained.⁵⁸ Another approach is to evaluate the amplitude of steady-state visual evoked potentials (SSVEPs). When, for example, two items on the monitor are flickering with slightly different frequencies in the alpha/beta range, the SSVEP amplitude is enhanced, when the participants shift their gaze to the corresponding light source.^{59,85} The system of Cheng and co-workers⁸⁵ uses 13 buttons arranged as a virtual telephone keypad, all flickering at different frequencies. The subject has to pay special attention to one of the flashing buttons in order to enhance the amplitude of the corresponding flicker frequency (SSVEP).

The implantation of a special electrode into the outer layer of the neocortex allows us to record multiple unit activity in patients. This activity in form of spikes can be transformed into a pulse train and, in turn, can be used for cursor control and selection of letters or other items on a monitor. Spelling rates of about three letters per minute are reported with patients.⁸⁶

14.6 IMPORTANCE AND IMPACT OF VISUAL FEEDBACK

A central issue in BCI development is the impact of the setup and presentation of feedback. The type of feedback used in early experiments with the Graz BCI paradigm provided information of a correct versus an incorrect response, as determined by the classifier, at the end of each trial.⁷¹ In general, when using such a discrete feedback presented with delay, no increase of classification accuracy was found over the course of additional sessions. Further advances in feature extraction methods, such as the implementation of AAR algorithms,⁷³ allow one to calculate the parameters concurrent to the data acquisition. In other words, it was possible to provide instantaneous, classifier-based feedback during defined time periods. This type of feedback indicates in real time how well two EEG patterns (representing, for example, two classes) can be discerned. Using such a continuous feedback system, a general enhancement of performance could be achieved.⁷⁴

In order to investigate the impact of a continuously present visual feedback on sensorimotor EEG rhythms during motor imagery, the ERD/ERS time courses of BCI sessions with high performance were analyzed. [Figure 14.10](#) displays ERD curves of BCI feedback sessions with left versus right motor imagery of two subjects,

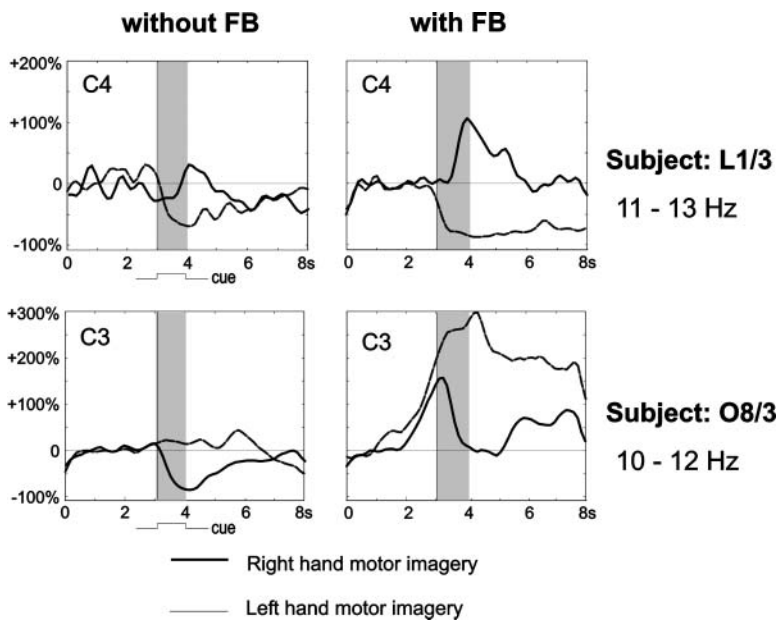


FIGURE 14.10 ERD/ERS curves of two subjects (L 1/3, 11–13 Hz; O 8/3, 10–12 Hz) for sessions without feedback (left panels) and with continuously present feedback (right panels). Data were recorded from the sensorimotor cortex (C3, C4) during imagined movements of the left (thin line) versus right (thick line) hand. The time period of cue presentation is indicated by a gray vertical bar.

and comparable data of control sessions without feedback. The initial recordings without feedback (left panels) reveal a transient desynchronization (ERD) of the mu rhythm over the contralateral hemisphere starting with the cue presentation. Continuously present feedback results in dramatic changes of the ERD/ERS patterns: both subjects show a clearly more pronounced difference between left and right motor imagery during feedback regulation. Instantaneous information may help the subject to test various strategies to manipulate the feedback bar and related EEG activity. Hence, these findings are in line with the general notion that feedback should be as fast as possible.⁸⁷

On the other hand, it is known that visual feedback may have positive as well as negative effects, and that these effects vary across subjects.⁸⁸ Correct responses are a source of positive reinforcement, which may lead to an enhancement of the target EEG pattern. Feedback of false responses, however, may elicit a negative emotional reaction, which in turn is likely to alter the EEG patterns in an unpredictable way. Further, the processing of the (moving) feedback stimulus may interfere with the mental imagery task, and may therefore, in some cases, impair the development of EEG control.

Hence, we should take into consideration the possible impact of the visual display itself (cursor, letter, etc.), which may cause further variations of the EEG patterns. There is evidence that sensorimotor rhythms do not become desynchronized

by visual stimulation.^{89,90} In contrast, even a localized augmentation of alpha band activity over sensorimotor areas was reported during visual processing.⁹¹ In a case where a subject watches a video film showing human movements, however, sensorimotor rhythms can display a significant decrease in power.⁹²

In animal studies, it was demonstrated that the observation of movement actions results in a strong activation in premotor areas.⁹³ So-called mirror neurons in area F5 displayed similar firing patterns, both when a monkey observed the experimenter's grasping movements and when the same motor action was performed by the monkey itself. The above-mentioned studies give strong evidence that a visual input, either used as target or as feedback stimulus in a BCI experiment, can modify the neuronal activity and sensorimotor rhythms in motor or related areas. Since most BCI systems are based on the processing of visual information (target presentation, cursor movement, selection of letters, etc.), the impact of the visual display on the sensorimotor activity is of particular interest, especially when motor imagery is used as a control strategy.

In a movement imagination experiment, the time course of EEG reactivity (ERD/ERS) in sensorimotor areas was studied based on multiple-channel EEG recordings. By analyzing and classifying single-trial EEG data by the method of common spatial patterns,⁷⁸ researchers found that a correct discrimination between right- and left-hand movement imagination was already possible 250 msec after the onset of the visual cue signalling the side of motor imagery.⁹⁴ This fast increase of classification accuracy after cue presentation can be interpreted as the result of a stimulus-specific and lateralized modification of sensorimotor rhythms. This finding, that two different visual targets (e.g., an arrow pointing to the left or to the right) can result in two distinguishable spatiotemporal EEG patterns as early as 250 msec after stimulus onset, is of special importance for BCI research and, possibly, opens up new ways of installing a fast communication channel between brain and computer.

14.7 THOUGHT TRANSLATION DEVICE: A CASE REPORT OF A COMPLETELY LOCKED-IN PATIENT

Patient E.M., a wealthy businessman from Lima, Peru, suffers from end-stage motor nerve disease. After diagnosis of the disorder at the age of 48, E.M. deteriorated rapidly and has been artificially respirated and fed for 4 years. Six months before initiation of training with the TTD, E.M. was diagnosed as completely locked-in and communication using assisted communication devices with eye movement control, heart-rate control, and EMG control had to be discarded. No voluntary eye movement was possible. The eyes of the patient were closed. Opening of the eyes was only possible by means of adhesive tape. However, testing of vision was impossible, and therefore a combined auditory-visual feedback and spelling system was used.

Figure 14.11 demonstrates that even the external anal sphincter could not be voluntarily controlled by E.M. An anal sphincter electrode was used and the patient was instructed to systematically contract (C) and relax (R) anal sphincter muscles. No single voluntary correct response could be recorded. In addition, several EMG locations were tested and the patient was asked to voluntarily increase and decrease

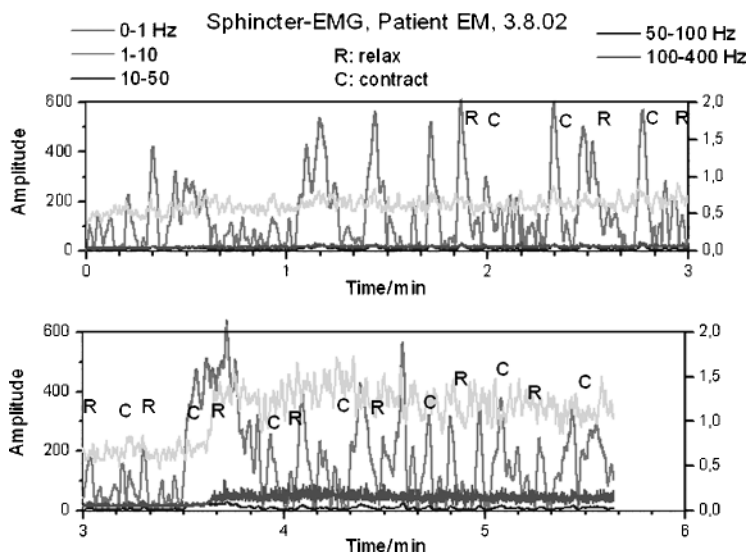


FIGURE 14.11 Recording of EMG from external anal sphincter of locked-in patient E.M. *R* indicates instruction to relax, *C* to contract.

EMG activity. Again, no successful voluntary motor control was possible. In order to test remaining cognitive abilities of locked-in patients a battery of cognitive tests using cognitive ERPs (as described by Kotchoubey et al.⁵⁵) were used in the case of E.M. The results of highly complex cognitive stimuli presented to E.M. and the recorded cognitive ERPs demonstrated intact or nearly intact cognitive potentials to complex verbal and nonverbal material. Therefore the diagnosis of a completely locked-in state could be confirmed on the psychophysiological as well as the neurological level. (Two independent neurologists diagnosed E.M. as completely locked-in.)

E.M. was first trained with the Tübingen version of the TTD by local technicians over a period of 1 month with daily training sessions of 1 to 2 hours' duration. His performance varied between 30% correct and 70% correct with an average of 52% — that is, chance level. No communication is possible if patients are unable to achieve significant control of positive or negative SCPs. Therefore, the Tübingen team, consisting of one physicist (T.H.) and two psychologists/neuroscientists (N.B. and H.F.) continued the training at Lima over a period of 22 days. A thorough behavioral analysis and an analysis of the motivational context of the training were conducted during that period, suggesting that most of the training difficulties of E.M. were motivational in nature. The presence of several family members with unclear motivation negatively affected the training progress. Other family members and trainers, interested in communicating with the patient, had a positive effect on training success. In addition, the expectation of rewarding activities such as changing locations strongly affected successful training. This and other results of the behavioral analysis and the motivational system underscore the necessity of a careful clinical

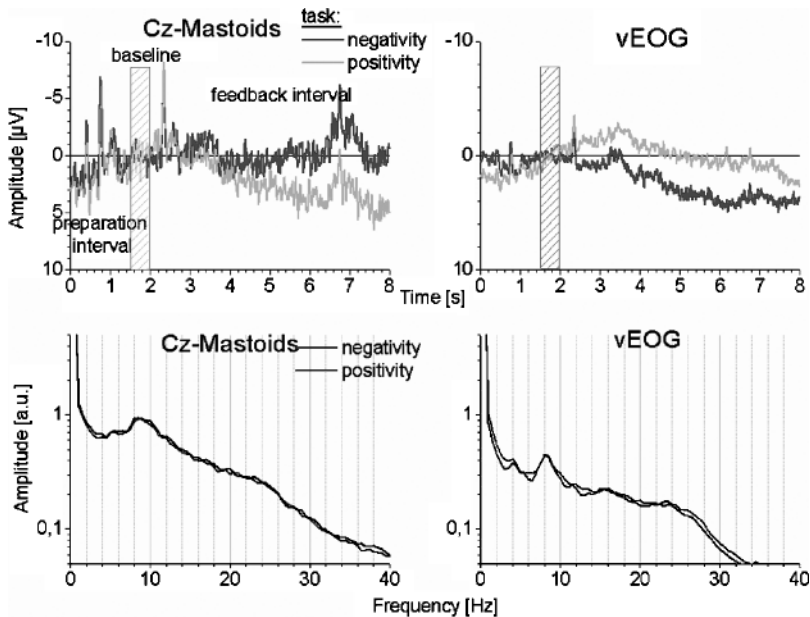


FIGURE 14.12 Averaged slow cortical potentials (SCPs) after 60 training sessions with locked-in patient E.M. (left, Cz), vertical electrooculogram (EOG) (right), EEG power spectrum (left below), and vertical electrooculogram (vEOG) power spectrum.

psychological evaluation of the patient and the patient's environment before BCI systems can be used in a clinical context.

In order to improve learning, a shaping procedure was introduced for training sessions before copy spelling or questioning of the patient was installed. Shaping consisted of rewarding the patient in a step-by-step manner for small improvements at the beginning and making the thresholds for achieving rewards more and more difficult. At the initial training session, the patient was rewarded for differentiation between positive and negative SCPs of only $1\ \mu\text{V}$, close to the noise level. After achieving a 70% correct response over 40 successive trials, the threshold was increased by 1 to $2\ \mu\text{V}$. Again the patient was trained up to 70% correct, and the next level of difficulty in SCP differentiation was introduced. If the patient did not succeed over a period of 40 trials, the threshold of reward was again reduced to the baseline. Figure 14.12 shows the average performance of the patient after 30 training sessions encompassing 200 to 400 trials per session. Average training success was significantly different from chance, but the average did not increase over 60% within the first 20 days of training by our team. Therefore, because of time constraints, copy spelling and questioning of the patient was introduced at a low but significant performance level of 60% correct differentiation between negative- and positive-tending cortical potentials.

Following the logic of lie detection and the assessment of criminal sceneries, a set of 40 questions was constructed (a BCI questioning system) and formulated in

Spanish so that the decisive and meaning-carrying word always arrived at the end of the question and each question was formulated in an affirmative or negative grammatical form. Questions of vital importance for the patient were mixed with neutral questions such as “The capital of Peru is Lima,” “The capital of Peru is Bogota,” “The capital of Peru is Santiago,” and “The capital of Peru is Asunción.” The auditory feedback of the SCPs lasting for 4 sec were changed such that not only a high-pitched tone for cortical negativity and a low-pitched tone for cortical positivity was presented, but also the word “yes” was repeated every half second during negativity and the word “no” was repeated every half second during cortical positivity. In addition, the television screen was brightly lit during negativity and darkened during positivity, providing the patient with continuous visual feedback of his ongoing cortical polarization even with closed eyes. The data show that the patient was able to answer these questions at a stable and significant level. In addition, copy spelling of several words was possible, but free spelling could not be achieved because of the high variation of correct performance related to motivational and behavioral effects. The training of this patient continues and progress will be reported in the future. However, the analysis of the data during the 3-week training session showed that at least “yes” or “no” communication on a high level of performance is possible with the completely locked-in patient.

14.8 EEG-BASED COPY SPELLING: A CASE REPORT

The following case history represents an attempt to employ the Graz BCI to establish an alternative communication channel for a severely paralyzed patient. It was demonstrated that this is not an impossible task, when patients suffering from advanced ALS acquired the ability to operate a spelling device by regulating their SCPs^{82,95} (see also [Section 14.7](#)). In some cases, however, even after several months of practice, no voluntary control of SCPs could be attained. Therefore, the question arose whether it was possible for such a patient to learn to control specific frequency components of the sensorimotor EEG by using an imagery strategy.⁹⁶

The male patient, 32 years old and diagnosed with cerebral palsy, suffered from a severe spastic form of tetraparesis and had lost the ability to speak. Regular training sessions for the patient were carried out at a clinic for assisted communications over a period of 22 weeks, supervised from the technical laboratory with the help of a “telemonitoring system.”⁹⁷ This system provided a direct access to the patient’s computer (a BCI system), enabling, e.g., visual control of the EEG data on-line, as well as a video conference connection that transmitted direct instructions to the patient and the caregiver as well as providing visual control of their behavior.

The EEG signal (5–30 Hz) used for classification or feedback was recorded from one bipolar channel over the left sensorimotor cortex and sampled at 128 Hz. To generate the feedback based on oscillatory components of the ongoing EEG, two approaches were used: (1) direct band power feedback (20–30 Hz), and (2) feedback calculated by a linear discriminant classifier, which was developed to discriminate between two brain states.⁷¹

The training period was divided into several steps involving both learning of the patient as well as adaptation of the system ([Figure 14.13](#)).

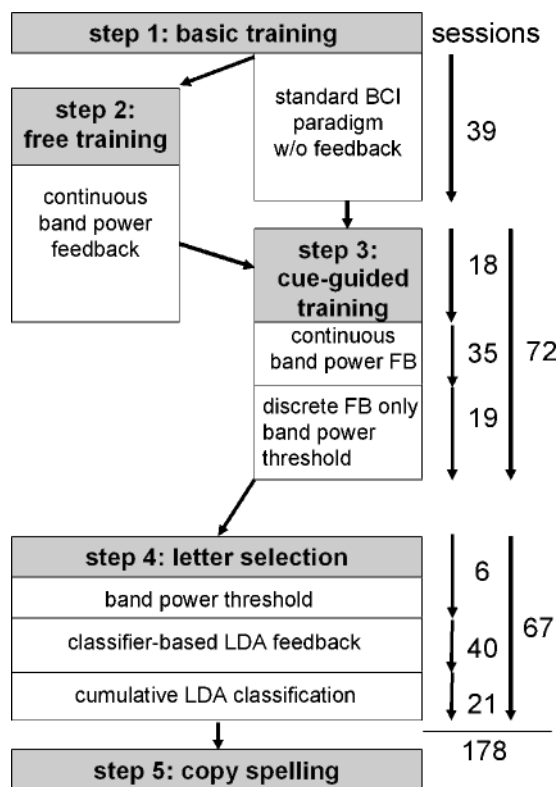


FIGURE 14.13 Diagram of training steps as described in the text, and corresponding number of performed sessions (right side). (From Reference 96, with permission.)

STEP 1: BASIC TRAINING

In the first sessions the patient was asked to perform various mental imagination tasks in response to a cue stimulus (the standard BCI paradigm, as described in [Section 14.5.2](#)). This denotes a search for the most efficient imagination strategy. No feedback was provided at this stage. The discriminating feature was a prominent, long-lasting desynchronization (ERD) of higher beta band components during imagination of right-hand movement, which was not visible during other imagination tasks. This led us to utilize upper beta band (20–30 Hz) activity for BCI control.

STEP 2: FREE TRAINING

In order to enhance the selected EEG components, a so-called “free training” was performed, where the band power (20–30 Hz) was continuously averaged over 4 sec and displayed on the screen as a vertically moving feedback dot (“cursor”). The patient was advised that imagination of right-hand movement moved the cursor downward (band power decrease, ERD). Relaxation, in contrast, either moved the cursor upward or caused it to remain in the center of the screen.

STEP 3: CUE-GUIDED TRAINING

The next step was to present visual cue stimuli (an arrow pointing up or down; standard BCI paradigm) and to ask the patient to move the feedback dot (cursor) in the indicated direction. The cursor position, based on the actual band power, was shown for a 4-sec time interval after cue presentation.

STEP 4: LETTER SELECTION TASK

Instead of the cue stimulus, two letters were presented, one near the top, the other near the bottom of the monitor. To select the upper letter, an increase in band power had to be produced by relaxing, whereas selection of the lower letter was achieved by motor imagery leading to band power decrease.

STEP 5: COPY SPELLING

In the final step the patient was confronted with a modified version of the so-called virtual keyboard⁷⁶ (see [Section 14.5.2](#)). His task was to copy words presented by the experimenter (copy spelling). Instead of single characters, a predefined set of letters, split into two equally sized subsets, was presented at the top and at the bottom of the monitor, respectively. When the patient was able to select the subset that contained the target letter, this subset was again split into two parts. This was continued until the patient selected the desired letter and, in a further step, confirmed this selection. During the first weeks of training in copy spelling, only correct selections were accepted by the system; false selections were measured for off-line analyses. This “error ignoring” mode was introduced in order to avoid the consequences of a wrong selection during training.

The on-line performance of letter selection, quantified as percentages of correct responses according to the classifier-based discrimination, indicated a significant learning progress from the first ten sessions (61.6%, SD = 5.3) to the last ten sessions (68.9%, SD = 5.4) of the training period. At the end of the reported training procedure, this patient was able to produce voluntarily two distinct EEG patterns, associated with motor imagery versus intended relaxing, and to use this imagery strategy for BCI control. With the achieved level of 70% accuracy in letter selection training, verbal communication was possible by means of a spelling device. This allowed the patient to write with a rate of approximately one letter per minute.

14.9 EEG-BASED CONTROL OF FUNCTIONAL ELECTRICAL STIMULATION IN A TETRAPLEGIC PATIENT: A CASE REPORT

The tetraplegic patient who participated in this study is a 28-year-old man who has been suffering from a traumatic spinal cord injury since 1998. He participated in BCI training with different types of motor imagery in order to check whether he was able to operate an orthosis or functional electrical stimulation (FES). After a number of training sessions with variations of the motor imagery strategy over a time

period of several months, imaginations of foot movement versus imagination of right hand movement achieved a classification accuracy of close to 100%.³²

Inspecting the EEG signals, it was found that foot motor imagery induced long trains of 17-Hz beta oscillations focused to the electrode position on the vertex (Figure 14.14). After thousands of foot movement imaginations, the midcentrally localized neural networks in the foot representation area and/or supplementary motor areas may be modified by motor imagery and may become able to generate oscillating activity in the beta band. This underlines both the importance of repeated BCI sessions with feedback and the plasticity of the brain.

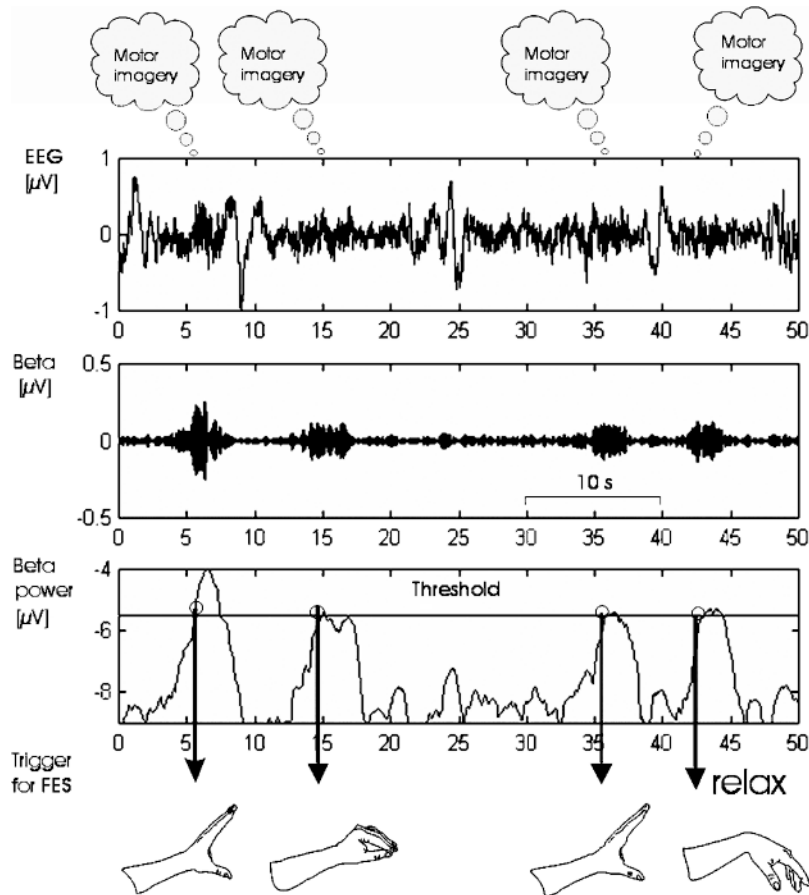


FIGURE 14.14 Example of the use of induced beta oscillations for control of functional electrical stimulation (FES) in a tetraplegic patient. The patient was able to induce bursts of beta oscillations by imagination of foot movement: Bipolar EEG recording from the vertex (overlying the foot representation area; upper trace), band pass filtered (15–19 Hz) EEG signal (middle trace), and band power time course (lower trace, arbitrary units) over a time interval of 50 sec. Threshold and trigger pulse generation according to FES and grasp phases are indicated.

With the mentally induced 17-Hz oscillations, a simple brain switch was constructed and used to control the functional electrical stimulation with three stimulation channels.³³ Whenever a 17 Hz beta burst was induced by motor imagery and the beta band power exceeded a predefined threshold, a trigger was generated. This trigger was used to switch the functional electrical stimulation. Surface electrodes placed on the forearm were used for stimulation of the paralyzed muscles. To realize a hand grasp, four basic muscle groups have to be activated: the finger and thumb extension for hand opening, the finger flexions for hand closing, the thumb flexion for grasping, and the wrist extension for stabilization of the hand. The individual grasp phases by induced beta oscillations are displayed in [Figure 14.14](#).

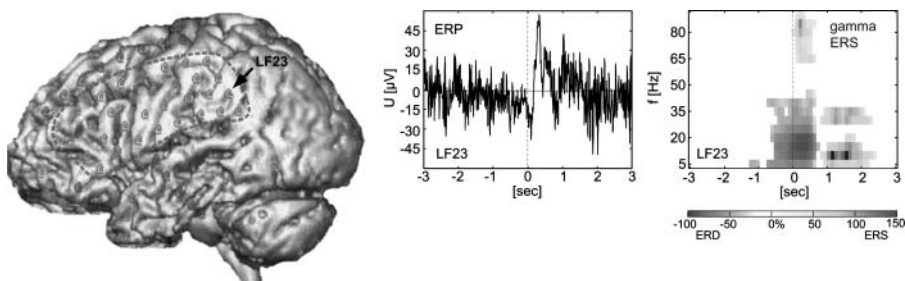
14.10 ECoG-BASED BCI: PRELIMINARY RESULTS ON CONTINUOUS ECoG CLASSIFICATION

In the future it will be important to develop asynchronous BCI systems, whereby internally paced “thoughts” may be classified continuously. Here we report on a preliminary study on the detection of movement-related patterns in single-channel ECoG signals. Twenty-two ECoG recordings (22 datasets) of seven subjects who participated in an epilepsy surgery program were used in this study. As part of their presurgical evaluation, they had 63 to 126 subdural electrodes implanted on the surface of their cerebral cortices. The subjects performed various movement tasks in a self-paced manner with at least 50 repetitions of each task. The intervals between successive repetitions were not less than 3 sec. The time course for each repetition was recorded by EMG electrodes to form a trigger channel. The trigger channel and the ECoG signals were recorded at a sampling rate of 200 Hz. A detailed description of the subjects, the electrode locations, and the data collection can be found in Levine et al.⁹⁸

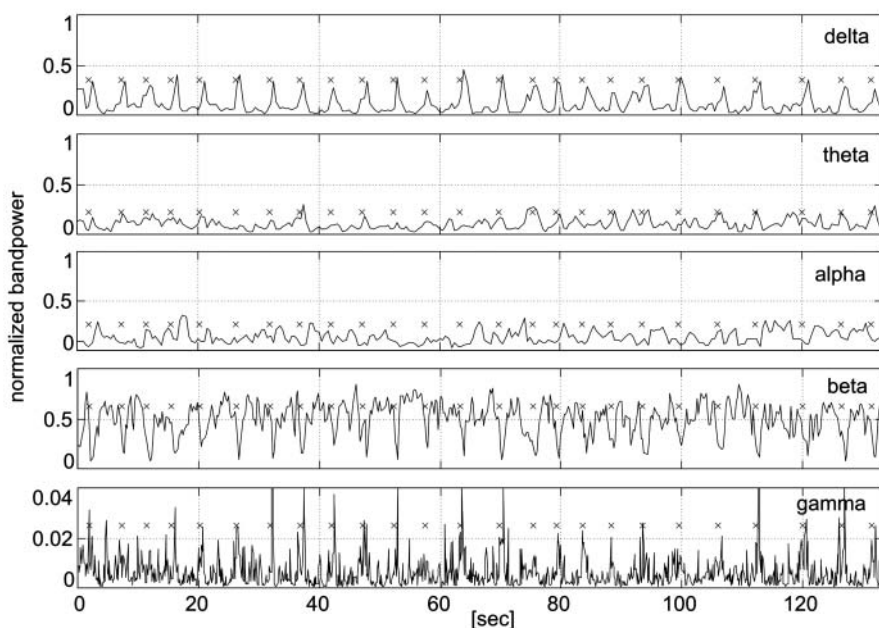
In order to obtain some insights about the data that could be used for the development of a detection system for movement-related patterns, time-frequency analysis with ERD/ERS maps and short-time Fourier time courses were performed. [Color Figure 14.15](#) shows an exemplary result of this time-frequency analysis for one channel. It illustrates that movement-related activity can occur in various frequency ranges in ECoG channels. Clearly, alpha and beta activity and evoked activity are present, but most interestingly, because it cannot be found in EEG, movement-related gamma synchronization can also be found. In four of the seven subjects, such synchronization was observed. The short-time Fourier time courses ([Color Figure 14.15B](#)) illustrate that the dominant frequencies are in the delta, beta, and gamma frequency range for this particular channel.

In general, all oscillatory patterns covered a very broad frequency range, which made it difficult to determine *a priori* which frequency components or features were most suitable for the detection of movement-related patterns. Therefore, a suitable feature extraction and selection method had to be applied to overcome this difficulty.

Wavelet packet analysis⁹⁹ was used to derive 18 features capturing the information contained in induced and evoked movement-related patterns.¹⁶ A genetic algorithm (GA), a stochastic search and optimization technique based on evolutionary computation,¹⁰⁰ was employed to weight these features according to their importance for



(a)



(b)

FIGURE 14.15 (see color figure) ERP, ERD/ERS map, and short-time Fourier time course of one exemplary ECoG channel. (a) ERP template calculated from 23 trials. This template was used for the cross correlation template matching (CCTM) method. The ERD/ERS maps represent averaged oscillatory activity in a frequency range from 5 to 100Hz. ERD is colored in red, and ERS is colored in blue. Movement onset is indicated by the vertical dash-dotted line. (b) The short-time Fourier time courses show ongoing normalized bandpower of movement-related patterns in the delta (<3.5 Hz), beta (12.5–30 Hz), and gamma (70–90 Hz) band. Theta (3.5–7.5 Hz) and alpha (7.5–12.5 Hz) bands do not show distinct peaks around movement onsets indicated by the crosses. (Modified from Reference 101, with permission.)

the detection performance and also to combine the six most important features in a linear fashion (associated with the largest weights) to obtain a one-dimensional feature signal.^{16,101} The actual detection was performed by a simple threshold detector

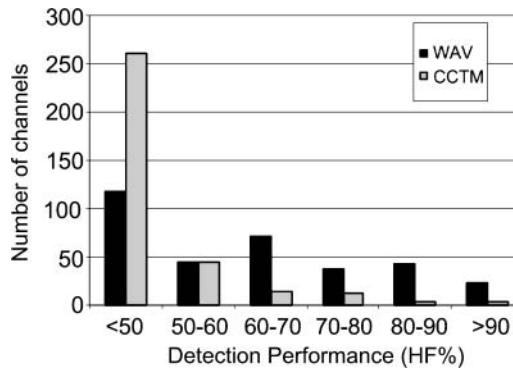


FIGURE 14.16 Histogram of the detection performance of all 339 ECoG channels investigated. The results are categorized into the following HF difference ranges (percentage of true positives minus percentage of false positives): $HF\% < 50$, $50 \leq HF\% < 60$, ..., $HF\% > 90$. (Modified from Reference 16, with permission.)

in way similar to that described by Levine et al.⁸ That is, detection points were defined as those points at which the one-dimensional feature vector exceeded an experimentally determined threshold. Any detection that occurred between 0.25 sec before and 1 sec after a trigger point was defined as a true positive (or a hit). Detection points outside of this interval were counted as false positives. The performance of the detection method for each ECoG recording was described by the percentage of the true and false positives. The true positive percentage was defined by the percentage of the triggers in the test data that were correctly detected. The false positive percentage was defined as the percentage of the detections that were not true positives.

The performance of the proposed method was evaluated off-line. More than 2 hours of data were analyzed. For 9 of 22 datasets, detection accuracies of more than 90% true positives and less than 10% false positives were found. Perfect detection (i.e., true positives at 100% and false positives at 0%) was achieved for 6 datasets. The mean and standard deviation (SD) of the true positive percentages of the 22 datasets (ECoG channels) analyzed by wavelets and optimized by a GA was $95.5 \pm 6.7\%$, and the corresponding mean $\pm$ SD of the false positive percentages was $9.2 \pm 9\%$. These results show that the proposed method can classify movement-related patterns in ongoing ECoG very accurately. This is remarkable, since only single channels were used as input for the method and spatiotemporal features of the ECoG recordings were not employed.

Figure 14.16 depicts the histogram of the results of all ECoG channels investigated for the wavelet-based approach and a method based on cross-correlation template matching.⁸ In the latter method, features are derived from ERP templates that are cross-correlated with the signal. Evidently, the wavelet method yielded improved results as compared with the cross-correlation template matching method. This can be seen as a consequence of the fact that the correlation template matching is based solely on the information contained in ERPs, while the wavelet-based approach employs the information contained in oscillatory activity as well. It is

interesting to note that for almost all of the best performing channels, the features associated with gamma activity had a substantial impact. However, this result should be interpreted cautiously, since there are no studies available that report on the gamma ERS of imagery data that would be required for a practical BCI. On the other hand, it can be expected that gamma oscillations may also be present during motor imagery because of the great similarity in cortical activation patterns between real executed and imagined movements.

14.11 WHICH INFORMATION TRANSFER RATE IS POSSIBLE WITH MOTOR IMAGERY?

The practical usability of a BCI system to control, for example, a spelling device or a virtual keyboard, would require a high system performance which can be measured by the classification accuracy or the information transfer rate (ITR) in bits per minute. The latter includes the accuracy of classification, the number of possible targets (classes), and the speed of selection.⁵⁶ In general, the accuracy declines when the class number is increased.

In a recent study, a new experimental paradigm was investigated to determine the optimal decision speed (trial length) individually for a subject using the Graz BCI.¹⁰² A simple game-like paradigm was implemented, in which the user had to move a falling ball into the correct goal (“basket”) marked on the screen. The horizontal position of the ball was controlled via the BCI output signal and the falling speed could be adjusted by the investigator. Four male volunteers (paraplegic patients) participated in this study. None of them had any prior experience with BCI. Two bipolar EEG channels were recorded from electrode positions close to C3 and C4. Two different types of motor imagery (either right versus left hand motor imagery or hand versus foot motor imagery) were used, and band power within the alpha band (10–12 Hz) and the beta band (16–24 Hz) were classified. After several training runs without feedback, the best imagery strategy was chosen and a linear classifier was set up. Feedback was given to the participants in the form of a falling red ball. After a pause with a fixed length of 1 sec, the little red ball appeared at the top of the screen and began to fall downward with a constant speed. This speed (i.e., the time the ball took to cross the screen) was varied by the investigator across runs between 5 and 1.5 sec. The patient’s task was to hit the highlighted basket (which changed sides randomly from trial to trial) as often as possible. Speed was increased run by run until the patient judged it as being too fast. The study attempted to find the optimal speed for a maximum information transfer rate. After each run patients were asked to rate their performance and to suggest whether the system operates too slowly or too fast. The highest information transfer rate of 17 bits per minute was reached with a trial length of 2.5 sec.

Theoretically, when the accuracy is 100% in a 2-class paradigm with motor imagery, an information transfer rate of 30 bits per minute is possible when the trial length is 2 sec (see also [Section 14.5.1](#)). A trial length shorter than 2 sec is problematical when oscillatory activity is used to control a BCI because desynchronization and synchronization processes of populations of neurons need time to develop. This time is in the order of seconds when alpha or mu rhythm is used for control.²¹

14.12 FUTURE DIRECTIONS

When the EEG is used as an input signal for a BCI system, multiple-channel recordings and special methods of preprocessing, such as, for example, independent component analysis (ICA), are recommended. Mu and central beta rhythms are especially suitable for ICA because both are spatially stable and can therefore be separated easily from other sources.^{101,103} Also, measures such as phase coupling and instantaneous coherence¹⁰⁴ should be incorporated, when multiple-channel data are available. The near future will show whether ICA as a preprocessing method and phase-coupling measurements can increase the reliability and the speed of a BCI. In addition, new processing strategies, as described for instance in [Section 14.10](#), could be of importance.

A clear-cut challenge for the future, furthermore, is to realize more effective BCI control paradigms, offering, for instance, a three-dimensional control over a neuroprosthesis or the operation of a spelling device with a speed of at least 5 to 10 letters per minute. Principally, both applications mentioned should be realizable either by the detection of firing patterns in intracortical recordings or the analysis of cortical potential changes by ECoG electrode strips or grids.

The advantage of the ECoG over the EEG is the better signal-to-noise ratio and therefore the easier detection of gamma activity. Recently, this was reported on bursts of gamma activity between 60 and 90 Hz in ECoG recordings during self-paced limb and tongue movements.^{28,29} These gamma bursts are short-lasting, display a high somatotopic specificity, and are embedded in the alpha and beta ERD lasting for some seconds. Examples of ERD/ERS time courses calculated in alpha and gamma bands during self-paced hand movement are displayed in [Figure 14.2C](#). Based on these gamma bursts it was also possible to detect individual finger movements in the ongoing ECoG with satisfying accuracy (asynchronous BCI mode;¹⁶ see also [Section 14.10](#)). Whether such gamma bursts also occur during motor imagery remains to be shown in ongoing research work.

Animal studies, focused on multiple-unit neuronal activity (the firing of groups of neurons) to perform two- and three-dimensional cursor control, are of special value for the realization of a multidimensional human BCI. The activity from a few primary motor cortex neurons in monkeys was used by Donoghue's group for two-dimensional cursor control.¹⁹ In contrary, Andersen's group in Pasadena made use of recordings from monkey parietal cells to control cursor movements.¹⁰⁵ Just by thinking about a reaching movement, and without actual movement execution, the position of a cursor could be changed.¹⁰⁶ Nicolelis' group reported a tracking task in more dimensions performed by monkeys, and demonstrated thereby the possibility of mental control of a three-dimensional robotic prosthesis.²⁰ They showed that motor control signals, associated with an arm movement, appear simultaneously in large portions of the frontal and parietal cortices and that, theoretically, each of these distributed cortical signals may be used separately to generate hand trajectory signals in real-time applications. The feasibility of direct cursor control for the selection of icons or letters using an implanted neurotropic cortical electrode was already demonstrated by Kennedy et al.¹⁰⁷

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